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Modularity Analysis of Makerspaces to Determine Potential Hubs and Critical Tools in the Makerspace

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Abstract

Globally, universities have heavily invested in makerspaces. Purposeful investment however requires an understanding of how students use tools and how tools aid in engineering education. This paper utilizes a modularity analysis in combination with student surveys to analyze and understand the space as a network of student-tool interactions. The results show that a modularity analysis is able to identify the roles of different tool groupings in the space by measuring how well tool groups are connected within their own "module" and their connection to tools outside of their module. A highly connected tool in both categories is considered a hub that is critical to the network. Poorly connected tools indicate insignificance or under utilization. Makerspaces at two universities were investigated: School A with a full-time staff running the makerspace and School B run by student-volunteers. The results show that 3D printers and metal tools are hubs at School A and 3D printers, metal tools, and laser cutters are hubs at School B. School B was also found to have a higher overall interaction with *all* the tools in the space. The modularity analysis results are validated using two-semesters worth of student self-reported survey data. The results support the use of a modularity analysis as a way to analyze and visualize the complex network interactions occurring within a makerspace, which can support the improvement of current makerspaces and development of future makerspaces.

Keywords

Makerspaces; Network Design; Engineering Education; Modularity; Bio-inspired

Introduction

Makerspaces have recently become integrated into a wide variety of engineering programs at universities worldwide [1]. This has drawn increasing attention as to how best to create an area where students gain hands-on experience [2, 3]. Several studies in the past few years have focused on barriers to entry and how tools vary in different makerspaces [4-6], identifying impediments to student use are often linked to a student's self-confidence, fear of failure, their training and mentoring [7]. Research has identified the need for rapid prototyping tools in makerspaces [8], however, the success of a makerspace as a result of other tools has not yet been established. Preliminary work used a bipartite network analysis to understand makerspaces as a tool-student network, providing a standardized system-level view of the space missing from standard survey-based investigations that can be expensive[9-12]. This paper continues that work, analyzing makerspaces using a modularity analysis to establish tool-student interaction patterns. This analysis approach is then compared to a conventional survey-based investigation for validation.

The work presented here tracks makerspace tool usage with surveys and log-in/check-out systems [10]. The tool usage data is quantified in a matrix and analyzed as a network using modularity analysis. Capturing interaction information in a matrix is used extensively in social science to understand how events impact actors, which in this case is how the tools connections to the students drive the interactions of the space [13, 14]. A modularity analysis is commonly used in ecology to analyze complex networks, such as plant-pollinator networks [15, 16]. Two metrics are calculated, participation and *z*-values, that classify the patterns among network connections and the nature of those connections. This process is able to identify critical network components, known as "hubs" with participation and z-values aiding in quantifying the tools interactions with the students in the network [16]. Hub plant species in a plant-pollinator network, for example, have a wide variety of bees interacting with the hub and linking different species together. Tools in a makerspace are viewed as analogous to plants and students to bees in a plant-pollinator network: students from different majors use the hub tools when interacting with the space. A modularity analysis has also been used for mapping complex air transportation networks, visualizing the most important air traffic locations and their connections, aiding in the understanding of air transportation networks [17]. Analyzing the student and their interactions as a network can provide a better understanding of the makerspace and enable alternate data collection and analysis techniques to be used beyond survey-based methods.

Methods

Survey Data Collection

The primary method for gathering results was through self-reported student surveys. The surveys consisted of end-of-semester surveys that focused primarily on the student's usage of the space throughout the semester. The order that students learned the tools and the classes students used the tools for were also self-reported in the surveys. This data was used to validate the modularity analysis results. Table 1 details the differences between the two universities and lists the tool categories. The nomenclature for the tools will be kept consistent in later parts of the analysis. Tool names are normalized between the two schools surveyed for consistency in comparisons. Table 2 shows the 11 general tool categories used for analysis along with a comparison of the tools at each school within that category. School A has more training before each of the tools can be used and did not teach laser cutting, while School B has fewer restrictions for tool usage and does teach the laser cutter. The difference in restrictions between the two schools is important to note when delving deeper into the analysis.

Slight modifications were made to the survey between the two semesters, such as increasing the variety of tools students could pick to better reflect the selection within the makerspaces. The main difference is that three categories (crafts, paint booth, and CAD station) were not included for School A in the Fall 2020 survey, but do show up in the Spring 2021 survey. These tools are not included in the modularity analysis for School A for the Fall 2020 semester.

Table 1: The tool list included in the surveys. Relevant differences between the two schools (A and B) are highlighted in terms of the barriers to their use (training required, course directed use, and no supervision required). Tools that were not part of the Fall 2020 survey for School A are denoted with * and for both Schools A & B with **.

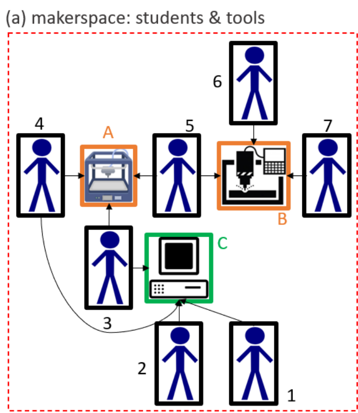
TOOL CATEGORIES		**Requires Training**		**Used by a Class**		**Student Use Without Supervision**	
		A	B	A	B	A	B
Tool 1	3D Printing	X	X	X	X	X	X
Tool 2	Metal Tools	X		X	X	X	X
Tool 3	Laser Cutter	X			X		X
Tool 4	Wood Tools	X				X	X
Tool 5	Handheld Tools			X	X	X	X
Tool 6	Electronic Tools			X	X	X	X
Tool 7	Studied at the Space					X	X
Tool 8	Got Help			X	X		
Tool 9	Crafting*	X					
Tool 10	Cad Station*	X		X	X		X
Tool 11	Paint Booth**					X	X

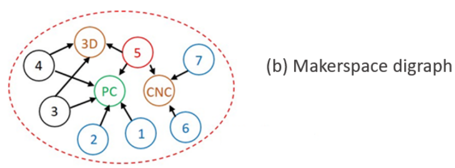
Table 2: Tool category breakdown with specific tools available in the space.

Tool Category	**Specific Tools Included**
(1) 3D Printing	Ultimaker 3D Printer, Formlabs Form 2 Printer, Stratasys 3D Printer, 3D Scanner Arm
(2) Metal Tools	Angle Grinder, Band Saw, CNC Metal Mill, Manual Mill, Manual Lathe, Drill Press, Belt Sander, Polishing Wheel, Table Vice
(3) Laser Cutter	Lasercutter
(4) Wood Tools	Band Saw, Belt Sander, Circular Saw, Miter, Jigsaw, Drill Press, CNC Wood Router, Router, Planer, Table Saw, Hammers, Measuring Tape, Hand Saw, Dremel
(5) Handheld Tools	Pliers, Vice Grips, Clamps, Screw Drivers, Hand Drills, Chisels, Tin Snips
(6) Electronic Tools	Circuit Board Plotter, Multimeter, Power, Supply, Soldering Station, Oscilloscope, Logic Analyzer
(7) Studied	Studied, Hung out, Met with a Group
(8) Got Help	Got Help From Makerspace Volunteer, Got Help From Someone Who Wasn't a makerspace volunteer, Gave Help
(9) Crafting*	Embroidery Machine, Sewing Machine, Vinyl/Paper Cutter, X-Acto Knife, Scissors, Glue Gun, Wire Cutters
(10) CAD Station*	Cad Station, Workbench, Whiteboards
(11) Paint Booth**	Paint Booth

Makerspace Network Creation

Survey data was used to map interactions between students and tools in a graph (Fig. 1b) and in a quantitively complete structural matrix (Fig. 1c) for the modularity analysis. The tool usage data from the surveys was converted into a bipartite network, which visualizes the connections between two groups: the students and tools [18]. A value of one or zero was used to quantitatively map these interactions into a matrix form (Fig. 1c), indicating if a student used a tool (one) or not (zero) [18]. An example interaction matrix with tool usage is shown in Figure 1a, with seven students interacting with three tools. The matrix in Fig. 1c quantifies the presence of interactions for the network shown in Fig. 1a, enabling a modularity analysis to then be conducted.





	3D Printer	CNC Machine	Computer
Student 1	0	0	1
Student 2	0	0	1
Student 3	1	0	1
Student 4	1	0	1
Student 5	1	1	0
Student 6	0	1	0
Student 7	0	1	0

(c) makerspace structural matrix

Figure 1: Bipartite network analysis with tool student interaction were a) is a hypothetical makerspace network with student-tool interactions, b) depicts this as a digraph, and c) shows the resultant bipartite interaction matrix. Figure used with permission from [9].

Modularity Analysis

A modularity analysis requires two steps: 1) creating modules and 2) calculating the participation and *z*-values [16]. Modules are calculated using the primary method with the MATLAB package BiMat, which allows for analysis of complex bipartite networks [19]. BiMat was used to identify sets of tools that students often use in combination with each other, assigning such tools to a module. The process takes an unordered, bipartite matrix and runs it through potential modular scenarios until it optimizes the modularity of the system [19]. Modularity refers to the degree that nodes in the network can be grouped into clusters with overlapping interactions. Modularity is calculated using Eq. 1, where E represents the total number of interactions between students and tools, Bij is the bipartite adjacency matrix (as shown in Fig. 1), and ki and dj represent the number of interactions for each individual tool and student, respectively [19, 20]. The δ function checks the module indexes of each student-tool pairing, yielding a value of one if the two actors are in the same module and a value of zero if they are not [21].

$$Q_b = \frac{1}{E}\sum_{ij}(B_{ij} - \frac{k_i d_j}{E})\delta(g_i, h_j) \tag{1}$$

The Newman/Leading Eigenvector method was used for optimization, as it generates a reproducible set of module assignments given consistent inputs [22]. This method starts with a two-module structure and identifies module assignments for each node that optimize modularity. Additional modules can then be added by repeating this process within each module, accepting a new subdivision only if it increases the modularity of the entire network [23]. All new modules are then checked again, with the final, optimal assignments determined when no additional subdivisions exist that would result in an increase in modularity.

The *connectivity* (*z*) and *participation* (*p*) values of Eq. 2 and 3 quantify how connected a particular tool is to the rest of the network. For these bipartite makerspace networks, tools and students act as nodes (N), while links between nodes represent the interaction of a specific student using a specific tool [24]. Since tools and students are both placed in modules within the space, all links between nodes can be classified as either links within a module or links between two modules. The k_i in Eq. 2 is the number of links of node *i* to other students/tools within its own module, *ksi* is the average number of links of each node (other tools/students) in the module, and σ_{ksi} is the standard deviation of k_{si}. The k_{is} in Eq. 3 is the number of links of node *i* (a specific tool) to other nodes in module *s* and k_i is the total number of interactions that node *i* has with other nodes [25].

$$z_i = \frac{k_i - k_{si}}{\sigma_{ksi}} \tag{2}$$

$$p_i = 1 - \sum_{s=1}^{N_M}(\frac{k_{is}}{k_i})^2 \tag{3}$$

While one tool may be in a module due to its dominant interactions, tools can still interact with tools outside of their module. As an example, while the mill and lathe may be used primarily by students who only use mechanical tools, there may still be students who primarily use craft tools but also the mill and lathe, thus creating a connection with tools outside of the mill/lathe's module. The *z* or *connectivity* value quantifies the *within module degree* of a tool or student. If many students that use the same set of tools are also all using the laser cutter, the laser cutter would have a high *connectivity* value. If within that same group of students only one of them had used the laser cutter it would have a low *connectivity* value. These metrics are calculated from the modular network matrix and quantify the patterns and characteristics of connections between students and tools in the space.

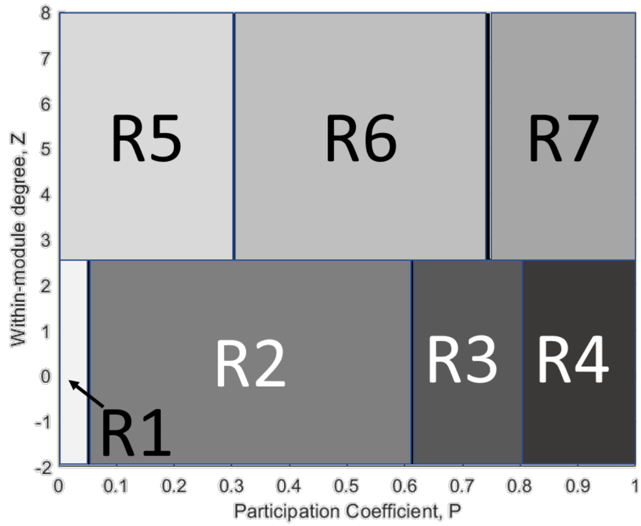


Figure 2: Modularity analysis sectioning determined by connectivity (*z*) and participation (*p*) values. The regions R1-7 specify the role that a tool and/or student has in a network, as described in the main text.

Equations 2 and 3 were plotted in Fig. 2, which illustrates the different regions as defined by the values of *p* and *z*. The regions describe seven different roles that students and tools can have within the space, and are used in network analysis as a cartographical representation of the roles in a complex network and better understand the functions of actors in the network [25]. The work here tests an analogy between makerspaces and mutualistic ecosystems, where the interactions between species groups (here students and tools) is mutually beneficial. Ecologists have classified each region as serving a different role for the network (or in this case, the students and tools). The cutoffs lines shown in Fig. 2 are non-trivial and come from the work of Guimerà and Amaral [25].

- **R1** ($p \approx 0$, $Z<2.5$): *Ultra Peripheral Nodes*, niche or rarely used tools
- **R2** ($p<0.625$, $Z<2.5$): *Peripheral Nodes*, tools that are not used as often
- **R3** ($p<0.8$, $Z<2.5$): *Non-Hub Connectors*, tools that interact heavily within their own module
- **R4** ($p>0.8$, $Z<2.5$): *Non-Hub Kinless Nodes*, tools critical to their own module
- **R5** ($p<0.3$, $Z<2.5$): *Provincial Hubs*, tools that interact with a variety of tools of different modules
- **R6** ($p<0.75$, $Z<2.5$): *Connector Hubs*, tools That interact heavily within their module and with other modules
- **R7** ($p>0.75$, $Z<2.5$): *Kinless Hubs*, tools that interact heavily with everything in the space and cannot be assigned a module

The seven roles in the space guide conclusions depend on where the tools/students fall when plotted. A tool in the R6 region is considered a *Connector Hub*, meaning it is critical to the space and interacts with a wide variety of students both in its own module as well as with other modules. A tool in the R1 region is considered an *Ultra-Peripheral Node* and is less important to the network's functioning, likely being a niche or rarely used tool.

Results

Tool Usage: Comparing Survey & Modularity Results

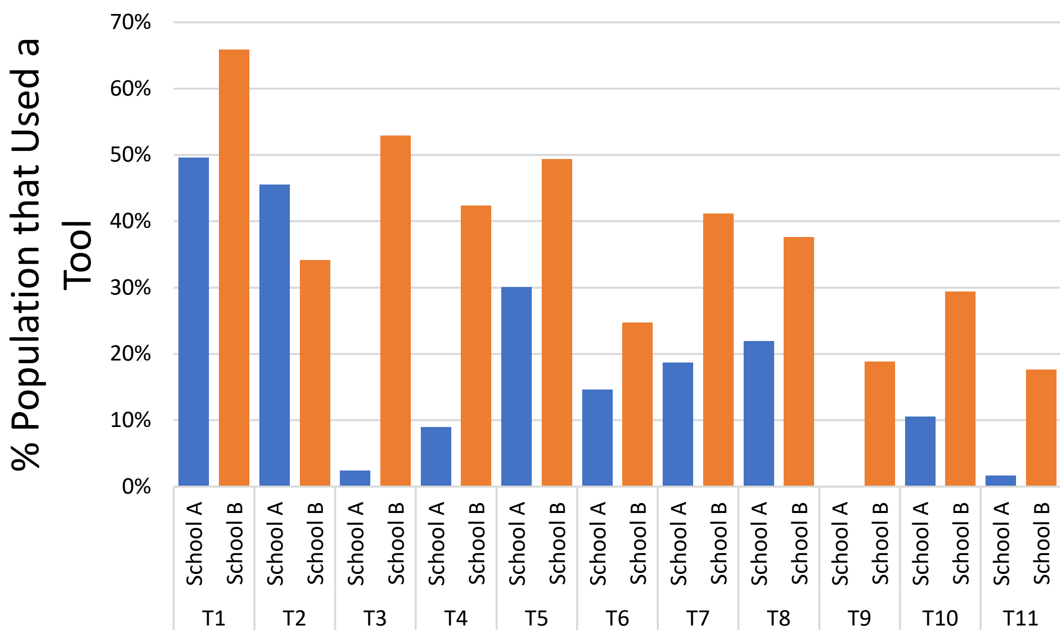


Figure 3: Proportion of students (as a % of total survey population) at School A (blue, N=123) and B (orange, N=85) that indicated using a tool out of all survey participants for Spring 2021.

Figure 3 highlights that there are substantial differences in the usage patterns at both institutions. School B has a higher overall tool usage than School A, with a particularly high usage for 3D printers, hand tools, and the laser cutter in both semesters. School A was found to have a relatively high 3D printer usage compared to its other tool groups. School A's metal room usage exceeded that of School B. Tools like laser cutters and craft-related tools had almost no usage at School A.

These tool usage patterns directly correlate with the modularity analysis results in Fig. 4, where key tools can be quickly identified from the interaction data. The results of the modularity analysis for both School A and School B are shown in Fig. 4. Figure 4 bottom left image shows that two tools in School A fall in the R1 region (the bottom left most quadrant, as described in Fig. 2), labeling them as ultra-peripheral nodes and indicating that very few students used the tool, if any at all. The relative spread of the data points in Fig. 4 is also an important indicator. At School B a majority of the tools investigated were found to be hubs. School A had a wider spread, with some tools highly used by both students within the same module and those from others (and therefor hubs) and others less so. The modularity analysis easily identifies these tool usage roles and highlights heavily used tools that connect across the space (hubs). These hub tools have high numbers of interactions with a wide variety of students, confirming the importance of the tool to the overall success of the makerspace. These tools that are found in region R7, the top right corner, of the plots in Fig. 4. Two major hub tools at School A are the 3D printer and the metal tools. Hub tools at School B are the 3D printer, laser cutter, and craft space.

Data about the order that students learn tools was also collected via surveys. The results of this question at both institutions can be seen in Fig. 5. The 3D printer, the manual mill, and the laser cutter at both schools were the tools that student most often reported as learning first, suggesting that these tools may act as a gateway into the space.

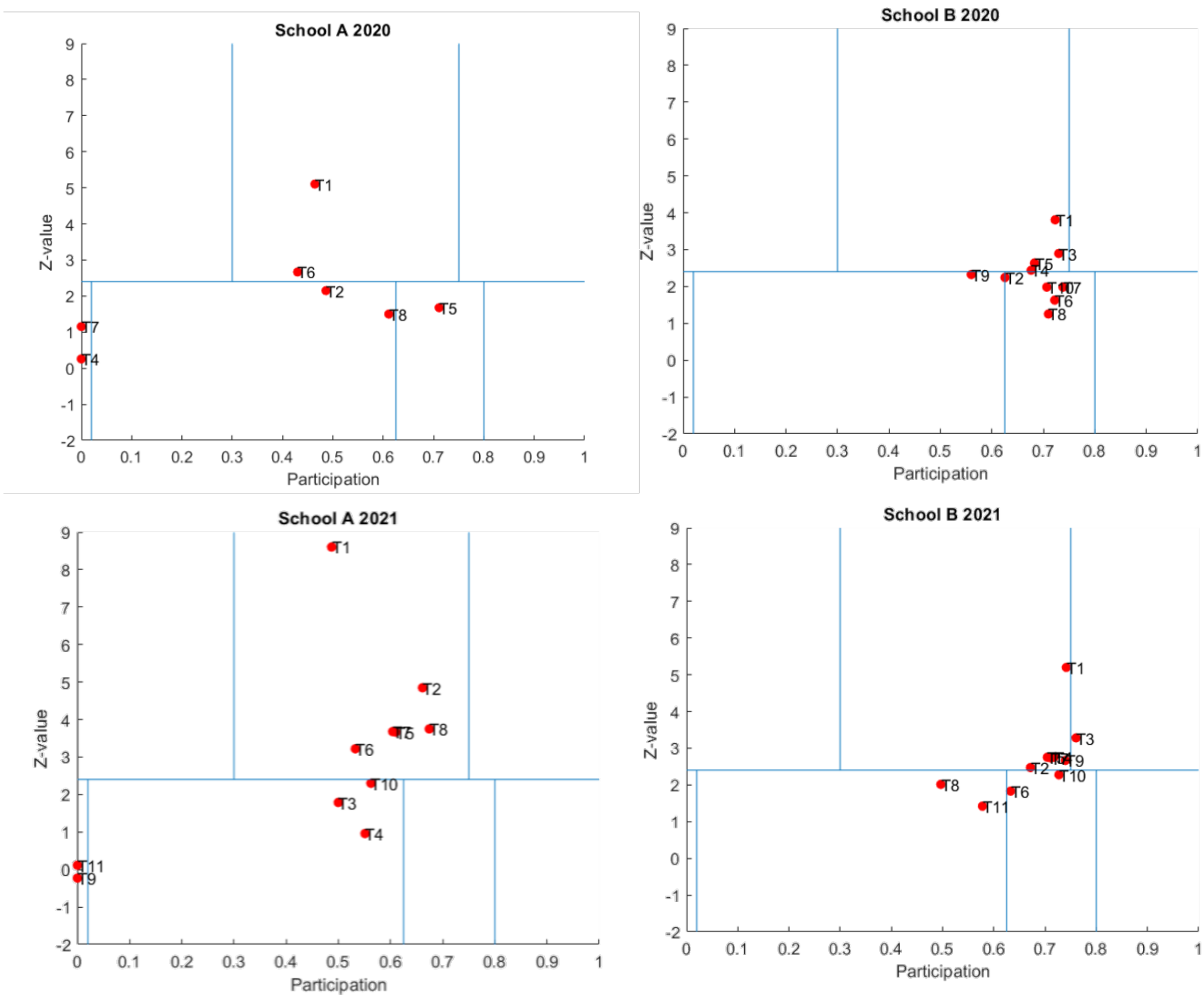


Figure 4: School A (left) and B (right) modularity analysis results between two semesters, Fall 2020 (top) and Spring 2021 (bottom). The regions delineated by the blue lines correlate with R1-7 as described in Fig. 2.

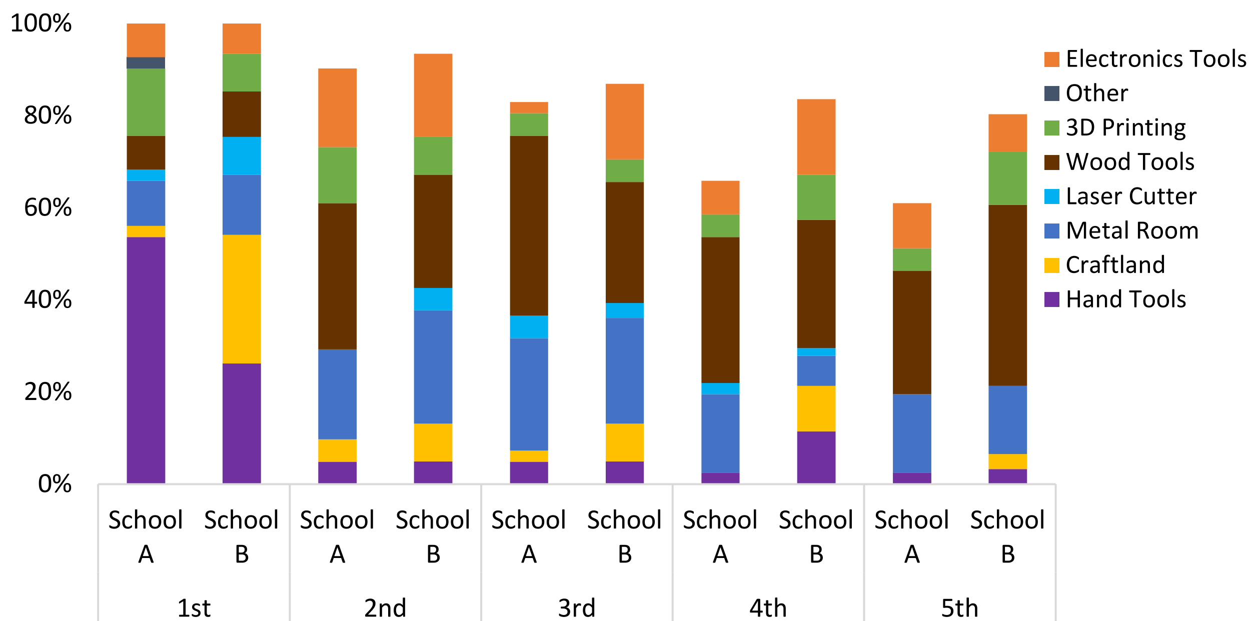


Figure 5: Categories of the first five tools learned by students at Schools A (N = 61) & B (N = 41) for Fall 2020, from self reported surveys.

Discussion

The modularity analysis quantitatively characterizes interactions within the makerspace, identifying high-impact tools (hubs) that serve as critical parts of the makerspace and low-impact tools that may need more support to encourage student use. A major advantage of this analysis is its ability to condense a vast amount of data and visualize it, as opposed to relying on more conventional methods that require far more analysis and graphics to convey the same information. With only a few graphs like those in Fig. 4, a modularity analysis can provide insight into both usage rates and the significance of tools for the successful functioning of the makerspace.

The modularity analysis for the two schools is also able to provide insight into differences between the makerspaces. The tools that were found in Fig. 4 to be hubs may be due to their use for specific courses. For both schools, tools that were used within a course (for example the 3D printers, mill, and lathe at School A, and the laser cutter at School B) tended to have a higher usage within the space. Additionally, for both schools, 3D printing was a major hub for students and one of the major tools that students used first. Another key difference is that School A is staff-run and School B is student-run. The overall higher interaction rate at the student-run space of School B may be a result of this configuration. This is evident in the modularity analysis as the tools in Fig. 4 fall closer to the left side of the graph (due to fewer interactions) for School A. The survey data also supports this claim, indicating that a smaller percentage of the total population at School A uses many tools in the space. This can be seen in Fig. 5 with a side by side comparison of the tools with School B having higher percentage of students using a majority of the tools, often more than a 10% difference with each tool between schools, with the only exception being the metal tools.

Figure 5 highights the survey results about the order that students reported learning tools. At both schools, students reported that the 3D printer, the manual mill, and the laser cutter were the tools they learned first, suggesting that these tools may act as a gateway for students into the space. Introductory engineering courses often promote these tools as they are relatively easy to learn and teach the fundamentals of CAD. These tools represent a relatively small portion of the later tools learned, as expected students progress to more niche and specialized tools over the years. Specialized tools may be less promoted by classes, resulting in their use being more dependent on a student's interest and hobbies.

The modularity analysis results are validated by the survey responses about percentages of tools used shown in Figure 3. Figure 3 shows that 3D printers and the lasercutter were the two highest use tools in the space for School B in 2021. Similarly, the modularity analysis shows the 3D printer as well as the lasercutter as hub tools with the highest participation and z-value. On the other hand for School A, the two least-used tools identified in the survey were craft tools and the paint booth. The modularity analysis gives these two the lowest participation and z-values out of all the tools investigated. This validation supports the ability of a modularity analysis to identify heavily used tools as well as tools not used as often, allowing for visualization of the roles and interactions of the tools in the network.

The survey data from both Fall 2020 and Spring 2021 are impacted by each school's COVID-19 related rules. As a result, the results are not entirely reflective of normal space use as access to was heavily restricted. At School A, students were only allowed to work on class projects with a select few clubs granted limited access to the space. Personal use was explicitly prohibited during this time, although this policy was not enforced particularly strictly. School B, on the other hand, had significantly fewer restrictions than School A. The restrictions that were in place at School B consisted of requests for social distancingand reduced capacity for the space as opposed to blanket bans on categories of usage. Due to these differences, it is imperative that a follow-up survey be conducted when Covid-19 restrictions are lifted from these spaces.

Future work will make slight modifications to the surveys to streamline tools that may have been added or removed from each of the spaces. Considering that self-reported frequency estimations have proved to be inaccurate, whether this dimension of the survey or not should be included is in question. That being said, whether such a change would render future surveys incomparable to the surveys herein and from previous semesters or not is a valid concern as well. The modularity analysis shown here primarily focuses on tools; however, the analysis can be expanded to learn more about the students who are using the tools. Expanding the general tool groups into specific tools can also provide a better understanding as to why certain tools may be considered hubs, such as Ultimaker 3D printers being used more than the Stratasys resin 3D printer. Further understanding of the student aspect of the makerspace is needed because the differences in student demographics and in the cultures of the spaces can also play a role in the space's use. This work, however, does supports theuse of a modularity analysis to identify key tools and student-tool interactions, the method courses use a makerspace, and space culture to make recommendations for current and future makerspaces. Understanding how class schedules and tool usage relates to makerspace usage is vital to our implementation of spaces can implement courses to promote certain tool interactions or expand on course curriculum to better use gateway tools and increase overall student use of the space.

Conclusions

Makerspace analysis investigating the aggregate of all tool-student interactions within a makerspace has not been previously conducted. The work within this paper demonstrates the utility of this style of analysis in characterizing university makerspaces. Understanding how different tools are being used in the makerspace allows for recommendations to be made to promote the tools that lead to advantageous learning outcomes. The research in this paper focuses on utilizing modularity analysis to better identify key role interactions with the space and identify potential "hub" tools. Analysis was conducted for two schools with different makerspace cultures, School A being run by staff and B primarily being run by students. Results from the modularity analysis revealed School A had a large number of tools that were not being used often with other tools acting as the "hubs" that would bring students in, primarily the 3D printer and the metal tools. On the other hand, in School B, most tools were being highly used in the space and many tools were considered hubs, with the 3D printer being the major huband the laser cutter as another hub. Several hypotheses regarding the difference between the two schools can be linked to the culture and to class schedule, as some tools are not as promoted by classes. Survey results expand on modularity analysis and corroborate the results discussed.

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